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Modeling stock market return volatility in the presence of structural breaks: Evidence from Nairobi Securities Exchange, Kenya

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ABSTRACT

This study sought to model the stock market return volatility at the Nairobi Securities Exchange (NSE) in the presence of structural breaks. Using daily NSE 20 share index for the period 04/01/2010 to 29/12/2017, the market return volatility was modeled using different GARCH type models and taking into account four endogenously identified structural breaks. The market exhibited a non-normal distribution that was leptokurtic and negatively skewed and also showed evidence for ARCH effects, volatility clustering, and volatility persistence. We found that by considering structural breaks, volatility persistence was reduced, while leverage effects were found to lead to explosive volatility. In addition, investors were not rewarded for taking up additional risk since the risk premium was insignificant for the full period. However, during explosive volatility, investors were rewarded for taking up more risk. Moreover, we found that risk premium, leverage effects, and volatility persistence were significantly correlated. The GARCH (1,1) and TGARCH(1,1) models were found to be the best fit models to test for symmetric and asymmetric effects respectively. While the GARCH models were able to provide evidence for the stylized facts in the NSE, we conclude that the presence or absence of these features is period specific. This especially relates to volatility persistence, leverage effects, and risk premium effects. Caution should, therefore, be taken in using a specific GARCH model to forecast market return volatility in Kenya. It is thus imperative to pretest the data before any return volatility forecasting is done.

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Introduction

In the wake of various global financial crises, the analysis of stock market return volatility has for a long time attracted the attention of academicians and practitioners. This is due to the role it plays in the stock market trading system. The stock market return volatility informs the stock price movement, which then correlates to the volatility in the entire stock market. Consequently, an unstable stock market will also impact on the stability of the financial sector of any economy (Sinha, 2012). Stock market return volatility may create an efficient and liquid market and thus it is not always destructive. Nevertheless, excess market return volatility may cause financial market crisis and crashes which affects both developed and emerging markets (Huwart and Verdier, 2013).

The change in the stock market return volatility is mainly caused by daily information in the market and the differences in the investor's perceptions and expectations. When stock market return volatility increases due to good news or bad news disseminated in the market, it reduces market efficiency and liquidity. The informed and uninformed investors will receive the news in most cases asymmetrically from informed traders to uninformed traders. Bad news will increase stock market return volatility much more than good news (Singh and Tripathi, 2016). This may be interpreted by investors as an increase in risk and thus demand high returns for holding the assets (Maqsood, Safdar, Shafi and Lelit, 2017).

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This volatility also known as the “conditional variance of an underlying asset” is unobservable (Tsay, 2010) and must be estimated in a model that best exhibit its time varying conditional variance. According to Engel (1982), financial time series are found to depend on their own past values (autoregressive), depend on past information (conditional) and exhibit non-constant variance (heteroscedasticity). Various models have thus been proposed since 1980’s to ensure that the best estimate is modeled. One such model is the renowned Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by Engle (1982). Since then various ARCH models have been proposed, in order to clearly model and forecast the time-varying conditional variance of a series. This is done by using historical unpredictable changes in the returns of that series. These models have been successfully applied in financial market research (Brooks, 2019). Since stock market return volatility changes over time (time varying), it requires estimation to be done over time. This has brought about common features of market return volatility, documented as the stylized facts. Stock market return volatility is expected to exhibit non normality, leptokurtosis, show volatility clustering and persistence and exhibit leverage effects (Cont, 2001). The volatility model should thus be able to capture the presence of these features in any stock market, explain the chronological pattern of volatility and have the ability to forecast future volatility. However, while the stock market return volatility is expected to exhibit volatility persistence, McMillan and Ruiz, 2009 and Arouri, Lahiani, Levy and Nguyen, 2012 among others note that ignoring structural breaks would lead to persistence being overstated or spur evidence of long memory. This will consequently impact negatively on risk and portfolio management decisions, since the amount of persistence will have a direct impact on the price of the asset.

Various studies have been done to model and forecast stock market return volatilities in developed and emerging markets, but no conclusive model can fit all stock markets and in all time periods. This is because equities from emerging markets have different features than equities in developed markets. Emerging markets are characterized by high sample average returns, low correlations with developed market returns, more predictable returns, and higher volatility. Despite this differences most studies have focused on the developed markets e.g Japan and the US and some developing markets like India. In the African continent, efforts have been made to model the stock market return volatility of various countries that include Nigeria, Sudan, Egypt and comparative studies on various African countries including Kenya. In Kenya, attempts have also been made to model the Nairobi Securities Exchange over the years. While these studies have confirmed the presence of the stylized facts, they give conflicting evidence for the stylized facts and the best fit model(s) for the Nairobi Securities Exchange (NSE). In addition Mc Millan and Thupayagale (2011) note that structural changes especially in Africa reflect country specific developments. In view of this divergence of findings, it was imperative to investigate; (i) whether the NSE exhibited the stylized facts on stock market return volatility? (ii) Which model(s) is/are best fit to forecast the stock market return volatility in Kenya?(iii) Whether volatility persistence changed in the presence of structural breaks? These issues were tackled through empirical investigation and the findings will help in the formulation of economic policies especially in regards to market return volatility forecasting, characterization of stock return for portfolio and risk management decisions and derivatives valuation. This is because structural breaks increases the risks for investors who are buying or selling with long horizons(Pettenuzzo and Timmermann, 2011).

The rest of the paper is structured as follows; The next section presents the relevant literature on stock market returns volatility modeling. The third and fourth sections presents the methodology, empirical data and analysis respectively, while results and discussion and conclusions are made in the fifth and sixth sections respectively.

Literature Review

Financial time series data for instance stock market return exhibit various characteristics that have been confirmed through empirical studies to be common characteristics or stylized facts (Cont, 2001). First, stock returns volatility exhibit fat tails, in other words leptokurtic. Secondly, stock return volatility is not independent over time but it exhibit long memory or persistency and thus it is possible to predict future stock returns. Thirdly, the autocorrelation function of absolute returns decay slowly as a function of time lag roughly as a power law. Fourthly, stock returns are negatively related to changes in stock return volatility an effect known as the leverage effect. Fifthly, stock return volatility shows high return volatility being followed by high return volatility and low return volatility being followed by low return volatility a characterisic known as volatility clustering. Lastly, stock return volatility exhibit gain or loss asymmetry in that the market exhibit large drawdown’s in the stock prices and stock index values but not equally large upward movements.

The Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by Engel in 1982 brought about a breakthrough in the modeling of stock market return volatility (Engel, 1982). He noted that financial time series depend on their own past values and past information and also exhibit non-constant variance (Engel, 1982). The ARCH model is a systematic framework where the shock to a security return should be serially uncorrelated and using a simple quadratic function with its lagged values, one can confirm its dependence. However, the ARCH model had some limitations that included; the determination of the number of lags, the value of the lags was too big and the non negativity constraints were being violated. Due to these limitations, the ARCH model has not been used for decades (Brooks, 2019). Various extensions have since been proposed to mitigate the limitations of the ARCH model.

The Generalized Autoregressive Conditional Heteroscedasticity(GARCH) model was developed independently by Bollerslev (1986) and Taylor (1986) and was aimed at solving the limitations of the ARCH model. It was based on the infinite ARCH specifications which reduced the number of lags from infinity to two. The model assumes volatility will respond to good and bad news symmetrically. This symmetric response was based on the fact that conditional variance is estimated from the function of lagged

residues which are squared thus the sign is lost. The GARCH models thus provide accurate volatility forecasts provided that volatility persistence is accurately estimated (McMillan and Thupayagale, 2011).

The GARCH in Mean (GARCH-M) acknowledges that any increase in risk for any investment should be rewarded with an increased return. In order to model this concept, one must let the return of a security to be partially determined by its risk. This led to the extension of the ARCH model by Engel, Lilien and Robins (1987) to the GARCH in Mean model. The model includes the standard deviation of the asset returns into the conditional mean equation, commonly referred to as a risk premium. If the risk premium is positive and significant, then an increase in risk will lead to an increase in return.

Due to the nature of the GARCH model to treat good news and bad news symmetrically, Engle and Ng (1993) summarized the effect of bad news (negative shocks) or good news (positive shocks) on the conditional variance and referred to it as the news impact. This led to the development of GARCH model extensions and thus the classification of GARCH models as being symmetric or asymmetric. The symmetric models include the GARCH and the GARCH-M models, while the asymmetric models include EGARCH, TGARCH, and PGARCH models among others.

In order to allow asymmetric effects between positive and negative shocks, Nelson(1991), developed the Exponential Generalized Autoregressive heteroscedasticity (EGARCH) model. While the symmetric models namely GARCH and GARCH-M models captured leptokurtosis and volatility clustering, they failed to capture the leverage effect. This led to the development of EGARCH model and other asymmetric models. The EGARCH model is superior to GARCH model in that the conditional variance is guaranteed to be positive regardless of the values of the coefficients because of the logarithms (Brooks, 2019). The leverage effects are confirmed by the relationship between current return and future volatility. If it is negative, then the market exhibits leverage effect. Most EGARCH computations use the conditionally normal error instead of the Generalized Error Distribution (GED) as proposed by Nelson (Brooks, 2019)

The Threshold GARCH(TGARCH) model was first developed by Glosten, Jagannathan and Runkle (1993) also known as GJR GARCH model and was also proposed by Zakoian (1994). The model relaxed the restrictions of conditional variance dynamics and instead revealed the leverage effect. It sets the threshold so that if the parameter of leverage effect is zero, then it collapses to the GARCH model. If it is positive, then bad news have a larger impact on volatility than good news and if it is negative, then good news have a greater impact on volatility than bad news.

The Power GARCH(PGARCH) model developed by Ding, Granger and Engle (1993) is able to estimate the conditional variance as well the conditional standard deviation. It aims at estimating the power term and not imposing it.

Over the years various studies have been done to estimate the stock market return volatility and in most cases using GARCH type models and daily data. These studies have been done on developed, developing and emerging markets with or without structural breaks.

Bhowmik (2013) evaluated the stock market volatility in the US using a multidimensional framework. He found that high returns implied there is high volatility, a country's depression and political turmoil increased volatility which led to a decrease in growth rate. Rapach and Wohar(2006) investigated the aggregate US stock return for structural breaks using regression models and found evidence of the breaks in most markets. They also found structural breaks in a multivariate predictive regression model of S&P 500 returns. Rapach, Strauss and Wohar(2008), investigated the role of structural breaks in modeling stock market return volatility on the daily returns for the S& P 500 market index and 10 sectors stock indices for the period 12/9/1989 to 19/1/2006. Using Iterative cumulative sum of squares procedure, they found multiple structural breaks. They found that while structural breaks are important in modeling stock market return volatility, they provide challenges in forecasting. However, they noted that for a good forecast in the presence of structural breaks, one can average the forecast from the different models estimated using different time periods. Ewing and Malik(2016) investigated the presence of volatility spillover between oil prices and the stock market in the US. Using daily data for the period 1/07/1996 to 30/06/2013, they found no volatility spillover when the structural breaks are ignored but found evidence of volatility spill over in the two markets after accounting for the structural breaks. The findings confirmed the findings of Moon and Yu(2010) who also found asymmetric and symmetric volatility spill over between the US and China markets in the post break period.

Malik, Ewing and Payne(2005) used weekly data for the period starting June 1992 to October 1999 on the Canadian Stock Market. They found evidence of structural breaks in the Canadian stock market and reported that volatility persistence was reduced when the structural breaks were incorporated in the GARCH model. Similar findings were documented by Arouri, Lahiani, Levy and Nguyen(2012) in their forecast of conditional volatility of oil spot and futures prices. They found that the magnitude of volatility persistence diminished significantly after adjusting for structural breaks. They also added that for a good forecast, models that incorporated structural breaks gave a better volatility forecast.

Goudarzi and Ramanarayan (2010) modeled the volatility of the Indian stock market using ARCH and GARCH models for the period starting 26/07/2000 to 20/01/2009 and found that GARCH (1,1) was best fit and that it explained the stylized facts satisfactorily. They later expanded their study to test for asymmetric volatility for the same period using TGARCH and EGARCH models. They found that returns react to good news and bad news asymmetrically thus presence of leverage effects (Gourdarzi and Ramanarayan,2011). These findings have been echoed by other studies on the Indian Stock Market at different time periods (Mishra

and Rahman, 2010; Mittal, Arora and Goyal, 2012; Vitayalakshmi and Gaur, 2013; Banumathy and Azhagaiah, 2015; Kulshreshtha and Mittal, 2015; Singh and Tripathi 2016). In the most recent study by Goyal and Kumar (2019), they modeled the stock market return using data for the period 01/01/2011 to 01/01/2017 using 12 market indicators. They reported that the styled facts differed based on the indicators. While they concurred with the findings of their predecessors, they also added that PGARCH showed a significant influence in terms of power on conditional spillover.

In a comparison study Mishra and Rahman (2010) modeled the dynamics of stock market return volatility using daily data for the period starting 1/05/1998- 30/09/2006 for India and Japan. They found that India had ARCH effects, the market was more predictable, had volatility persistence, good news affected market return volatility than bad news and it was less efficient than the Japan stock market. On the other hand, the Japan stock market was more efficient than India, less predictable, had no ARCH effects, was affected more by bad news than good news and had volatility persistence. The findings of this study support the view that developed stock markets are much more efficient than developing and emerging markets.

Babikir, Gupta, Mwabuta and Sekyere (2012) studied the effects of structural breaks using GARCH models in South Africa for the period 02/07/1995-25/08/2010 using in sample and out of sample data series. They found presence of structural breaks and reported that structural breaks are important in modeling stock return volatility in South Africa. However, they noted that though structural breaks were relevant, there were no gains in using models that accounted for the breaks and that the GARCH models with expanding windows were sufficient. They found high volatility persistence and variability in the parameter estimates of GARCH (1,1) across all the subperiods.

Ogum, Beer and Nouyrigat (2005) studied the daily emerging market volatility for Nigeria and Kenya for the period 1988-1998 using EGARCH model. They found that in Kenya, there was positive and significant asymmetric volatility, returns were predictable and there was volatility persistence. While the findings were replicated by the Nigerian stock market, there was also presence of significant and positive risk premium in Nigeria unlike in Kenya where it was negative and insignificant. On the other hand, Adesina (2013) used monthly data for the period starting January 1985 to December 2011 to study the Nigerian stock market. He found that there was presence of high volatility persistence that is, past volatility influenced current volatility but there were no leverage effects in Nigeria.

Ahmed and Suliman (2011) modeled the stock market volatility of Sudan using GARCH models for the period starting January 2006 to November 2010. They found that asymmetric models were better than symmetric models, volatility was explosive, risk was rewarded by higher returns and there were leverage effects. These findings were confirmed by Abdalla and Winker (2012) who modeled the stock market return volatility for Sudan and Egypt for the same period. In addition the Egyptian market exhibited volatility persistence. The Egyptian stock market also exhibited leverage effects (Elsayed, 2011) and EGARCH was the best fit model (AbdElal, 2011).

Alagidede and Panagiotidis (2009), modeled stock market return volatility in a comparison study among African countries namely Egypt, Nigeria, Morocco, Kenya, South Africa, Tunisia and Zimbabwe. They found that there exist a risk premium in all the markets and that volatility was high for less liberalized markets. Kuttu (2014) investigated the return and volatility dynamics of four African countries namely Ghana, Kenya, Nigeria and South Africa. He found that there exist reciprocal return spillover between Ghana and Kenya, volatility innovations of Ghana, Kenya and South Africa emanated from the Nigerian stock market though their own volatility was more pronounced. They also found volatility asymmetry in Ghana, Kenya and South Africa but not in Nigeria. However, all markets exhibited volatility persistence. McMillan and Thupayagale (2011), measured volatility persistence and long memory in the African Stock markets and found that volatility persistence and long memory are exaggerated when structural breaks are ignored, accounting for time varying unconditional variance provides useful information that help improve volatility forecasting and there are different long-term stochastic volatility behavior between developed markets and African stock markets.

Empirical evidence from the foregoing cross country studies implies that the Nairobi Securities Exchange (NSE) exhibit predictable returns, volatility persistence, and positive and significant asymmetric volatility. However, the question whether the market rewards increased risk is still not conclusive as Ogum *et. al.* (2005) states that there is a negative and insignificant risk premium meaning risk is not rewarded by increased return while Kuttu (2014) report existence of a risk premium meaning that an increased risk will lead investors to demand a higher return. In order to get a deeper glimpse of the differences we reviewed different country specific findings for different time periods.

Nyamongo and Misati (2010) modeled the time varying volatility equities in Kenya using daily data for the period starting January 2006-April 2009 using GARCH(1,1), TGARCH(1,1) and EGARCH(1,1). They found that equity returns are symmetric but leptokurtic, volatility was highly persistent, there was insignificant leverage effect and the impact of news on volatility was not significantly asymmetric.

Wagala, Nassiuma, Islam and Mwangi (2011) modeled the stock market return volatility using weekly data for three firms listed at the NSE for the period 1996 – 2011. They found that the best fit model is IGARCH with t-distribution but noted that the model was unable to capture asymmetry which was captured by EGARCH (1, 1) and TGARCH (1, 1) models. They also noted that bad news increases volatility of the NSE index while good news increased the volatility of individual stocks.

Achia, Wangombe and Anyika (2013) studied the impact of political climate on market volatility using the NSE 20 share index for the period 1998-2007. They found that ARIMA (1, 1) and GARCH (1, 1) is best fit to model market return volatility in Kenya.

Mekoya (2013) in his study on the modeling and forecasting of stock market volatility at NSE used daily NSE 20 share index for the period 1/07/2001- 30/06/2013. They found that the market is not efficient in pricing risk and changes in stock returns are dependent on past information and therefore can be used to explain expected volatility. They also found evidence of volatility clustering and high returns respond to low volatility using GJR GARCH model. In addition EGARCH showed that there is asymmetric news impact on volatility.

Chege, Othieno and Kodogo (2014) studied the return volatility and equity pricing for the period January 1998 to December 2013 using GARCH-M and EGARCH. They found that equity returns shocks are highly persistent, the market exhibit volatility clustering around major world and domestic economic episodes and conditional variance is driven by past conditional variance. In addition, the investors demand higher returns for high levels of risk.

Ombamba (2015) investigated the dynamics of stock return volatility and leverage effects on share prices in Kenya using ARCH (1,1) and EGARCH (1,1) for the period 2/01/2010-31/12 2013. He reported that the NSE is not a weak efficient market, stock returns are negatively related to market volatility and the NSE exhibit volatility clustering and leverage effects but the effects are not persistent.

Koima, Mwita and Nassiuma (2015) estimated volatility of stock prices using GARCH model and the daily share prices of Barclays Bank of Kenya. Using data for the period 01/01/2008 to 10/10/2010, they found evidence for time varying stock return volatility, and negative return shock increases volatility than positive returns shocks.

Ndwiga and Muriu (2016) analyzed the dynamics of conditional stock returns volatility for the period 2/01/2001- 31/03/2014 using symmetric and asymmetric models. They found that the NSE returns are predictable, the market volatility effects on the stock returns are not explosive, the market rewards increased risk, the market exhibit volatility clustering, and there is a day of the week effect on Thursday and Tuesday due to the sale of government securities. It was also noted that new regulations reduce volatility clustering, impact of negative shocks and volatility persistence, while conditional volatility is reduced by daily mean.

Maqsood, Safdar, Shafi and Lelit (2017) modeled the stock market volatility using symmetric and asymmetric models for the period 18/03/2013 and 18/02/2016. They reported that the NSE exhibit high volatility clustering, highly persistent volatility, leverage effects and risk premium. They concluded that asymmetric models are able to model the market volatility much better than symmetric models and that the best fit model is the TGARCH (1,1) model.

It is worth noting that while countries such as India, Japan, Egypt, Sudan, and Nigeria show consistency in the findings on modeling time varying market return volatility, we cannot conclude the same in regards to the Nairobi Securities Exchange (NSE). Empirical evidence concurs that the NSE exhibit asymmetric time varying volatility, exhibit volatility clustering, and has predictable returns. Except for Nyamongo and Misati (2010), the NSE demonstrates presence of leverage effects, and asymmetric news impact where it is mostly bad news that increases volatility than good news.

On the other hand, the empirical findings differ on a number of issue that include, volatility persistence, existence of a risk premium and the model(s) that are best suited to forecast stock market return volatility. According to Ogum *et. al.*, 2005; Nyamongo and Misati, 2010; Kuttu, 2014; Chege *et. al.*, 2014; and Maqsood *et. al.*, 2017, they concluded that the NSE exhibited high volatility persistence. On the contrary, Ndwiga and Muriu (2016) found evidence for volatility persistence at the NSE but not highly persistent. In addition, Alagidede and Panagiotidis (2009), Chege *et. al.*, (2014), and Maqsood *et. al.*, (2017), note that the investors demand a high return for taking more risk. The findings differ with those of Ogum *et. al.*(2005) who found an insignificant and negative risk premium. Moreover, with all the studies done in Kenya using daily data for different periods except Wagala *et. al.*, (2011) who used weekly data, there is no conclusive evidence for which model is best fit to model the stock market return volatility. While most studies are silent, other findings report that IGARCH (Wagala *et. al.*, 2011), ARIMA and GARCH (Achia *et. al.*, 2013) and TGARCH (Maqsood *et. al.*, 2017) are the best fit models for modeling NSE stock market return volatility. In addition, EGARCH and TGARCH are best fit in capturing the asymmetry effects (Wagala, *et.al.*, 2011).

In addition, while attention has been given to modeling stock market return volatility in various countries, there is limited knowhow especially in Kenya on the impact of structural breaks in modeling this return volatility. The existing literature suggest that modeling stock market return volatility in the presence of structural breaks, reduces volatility persistence, help to detect presence of volatility spillover, explain volatility dynamics and provide better out of sample forecast in derivative pricing (Malik, Ewing and Payne, 2005; Rapach, Strauss and Wohar, 2008; Moon and Yu, 2012; Arouri, Lahiani, Levy and Nguyen, 2012; Ewing and Malik, 2016;). This implies that inferences about economic relationships can be misleading, forecast can be inaccurate and policy recommendations can be biased if structural breaks are ignored.

Research and Methodology

The study employed daily NSE 20 Share Index for the period 04/01/2010-29/12/2017 obtained from the Capital Markets Authority (CMA). The data was then converted to its natural logarithm where

$$r_t = \ln \frac{P_t}{P_{t-1}} \quad (1)$$

where the daily closing index is P_t , daily closing index for the previous day is P_{t-1} and \ln is the natural logarithm.

The descriptive statistics were estimated to give a preview of the data by testing for mean, standard deviation, kurtosis, skewness and Jarque Bera test for normality. The series was then tested for structural breaks using Bai and Perron(1998) multiple breakpoints test and the dates confirmed using a Chow breakpoint test. The Bai Perron test tested for global L breaks versus none at 5% level of significance and with a trimming percentage of 15%.

The series were run for stationarity test using Kwiatowski, Phillips, Schmidt and Shin (KPSS), (1992) model using Barlet Kenet estimation method and Newey- West Bandwith and the findings compared with those of Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979).

Where the KPSS Lagrange Multiplier (LM) statistic value was smaller than the critical value, the null hypothesis was not rejected thus the series was confirmed stationary. Where the KPSS LM statistic value was greater than the critical values, the null hypothesis was rejected thus the series was confirmed to have a unit root.

Where the ADF test statistic was less than the critical value, then the null hypothesis of a unit root was rejected and where the ADF test statistic was more than the critical values then the null hypothesis of a unit root was not rejected.

Once the variables were confirmed to be stationary, it was imperative to test for presence of ARCH effects in the return series residuals for each of the period. This was done to establish whether it was necessary to use GARCH type models. We used serial correlation Lagrange Multiplier (LM) test proposed by Engel (1982). The ARCH-LM was specified following Kulshreshtha and Mittal 2015, where we first obtained the residuals from the Ordinary Least Square regression of the conditional mean equation, which takes the form of an autoregressive moving average (ARMA) equation. We then tested the null hypothesis that there are no ARCH effects in the residual series.

Model specification

In order to properly model the NSE 20 Share Index, we calculated the optimal lag length using Log likelihood criterion, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan Quinn criterions. The GARCH model with the least value of information Criterion was chosen as the optimal or the best fit model for the Nairobi Securities Exchange. The models were also tested for ARCH effects to determine whether they were well specified for the period under study using ARCH LM test at two lags.

The study used both Symmetric (GARCH and GARCH-M) and Asymmetric (EGARCH, TGARCH, and PGARCH) models.

The GARCH model allows for both autoregressive (AR) and moving average (MA) into the conditional variance (Enders, 2015) that is it combines the mean equation and the conditional variance. We therefore specified the model as follows;

$$\text{Mean equation; } r_t = \mu + \varepsilon_t \quad (2)$$

Where; r_t = return at time t μ = mean of the returns ε_t = residual return at time t

$$\text{Conditional variance equation; } \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

Where; σ_t^2 -conditional variance at time t, ω - mean of unconditional variance, ε_{t-1}^2 -squared error at time $t-1$ from the mean equation (ARCH term), α_1 -First ARCH parameter, β_1 -First GARCH parameter, σ_{t-1}^2 -the last period forecast variance (GARCH term).

For the GARCH model to be well specified the constraints $\alpha_1 \geq 0$ and $\beta_1 \geq 0$, must be satisfied so that σ_t^2 is strictly positive. The short term dynamics of the volatility time series are determined by the size of these two parameters. The conditional variance is therefore said to be persistent if the sum of these parameters is equal to one. This means that there will be a long term or permanent change in all the future values if there is any shock in the market.

The GARCH-M is an extension of the GARCH model and just like the GARCH model it specifies both the mean and conditional variance. The GARCH- M was thus specified as;

$$\text{Mean equation } r_t = \mu + \lambda \sigma_t^2 + \varepsilon_t \quad (4)$$

Where; r_t = return at time t μ = mean of the returns ε_t = residual return at time t, λ is the risk premium,

Conditional variance equation; $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

When λ is positive it means that return is positively related to risk. It implies that an increased risk or volatility will lead the investors to demand for a higher return. Thus the risk premium is assumed to be an increasing function of the conditional variance ε_t , the higher the conditional risk the higher the return (Enders, 2015).

The GARCH and GARCH- M models are unable to capture the asymmetric attributes of financial data. The symmetric models assume that good news and bad news of the same magnitude have the same effect in market. This is incorrect since in most cases, bad news is seen to have a higher effect than good news. In equity returns this is attributed to leverage effect (Nelson, 1991). Thus we also modeled the market return volatility using asymmetric models as follows;

The EGARCH model is superior to the GARCH model for two reasons. First, since the $\ln \sigma_t^2$ is modeled, even if the parameters are negative, the conditional variance will be positive. Secondly, it allows for asymmetry since γ will be negative if the relationship between volatility and return is negative. We specified the model as follows

$$\ln(h_t) = \ln \sigma_t^2 = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right\} \sqrt{\frac{2}{\pi}} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (5)$$

Where the conditional variance parameter is $\ln \sigma_t^2$ and the asymmetric or leverage parameter is γ . The leverage parameter is expected to be negative so that bad news or negative shock increases future volatility while good news or positive shock reduces the effect on future volatility. When $\gamma \neq 0$, then there is leverage effects in the market.

The TGARCH model is similar to the GARCH model but with an extension to cater for the asymmetry. We specified the model as follows;

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (6)$$

Where, ω , α_1 and β_1 are the conditional variance non negative parameters to be estimated, and d_t is the dummy variable,

That is $d_{t-1}=1$ if $\varepsilon_{t-1} < 0$ bad news

=0 if $\varepsilon_t \geq 0$ good news

γ is the parameter that captures asymmetric/ leverage effect if $\gamma > 0$. When the shock is positive or its good news, the effect on volatility is given by α_1 . However, if it is a negative shock or bad news, the effect on volatility is given by $\alpha_1 + \gamma$. If the parameter γ is positive and significant, then negative shocks have a larger impact on σ_t^2 than positive shocks. If $\gamma = 0$ then the model collapses to a GARCH model.

The PGARCH model estimates the standard deviation instead of the variance. Instead of imposing the power, it estimates it as δ . It also includes the leverage effect parameter γ to test for asymmetry up to order r (Floros, 2008). We specified the model as;

$$\sigma_t^\delta = \omega + \beta_1 \sigma_{t-1}^\delta + \alpha_1 (|\varepsilon_{t-1}| - \gamma_1 \varepsilon_{t-1})^\delta \quad (7)$$

Where α_1 and β_1 are the ARCH and GARCH parameters respectively. γ is the leverage parameter and δ is the power term parameter. When $\delta=2$, then the model collapses to the GARCH model that allows for leverage effect and when $\delta=1$ then the conditional standard deviation is estimated instead of the conditional variance (Zivot, 2008).

Empirical data and analysis

Daily data for NSE 20 share index was collected from the Capital Markets Authority for the period 04/01/2010-29/12/2017 which gave 2002 observations. The data was analyzed using Eviews 10 statistical package. The raw data was plotted as shown in figure 1.

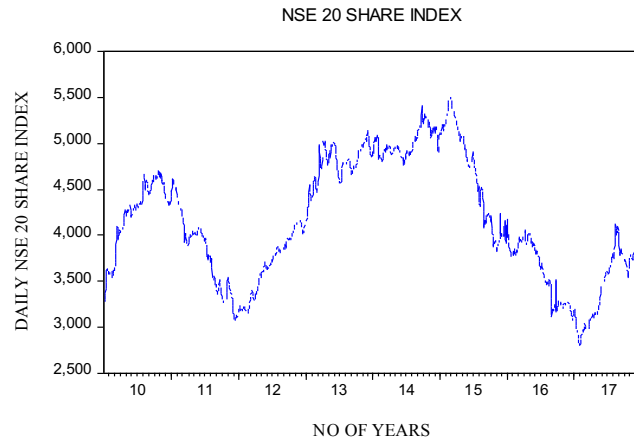


Figure 1: Daily NSE 20 share for 04/01/2010-29/12/2017

Data description

The characteristics of the data in terms of mean, maximum and minimum value, standard deviation, kurtosis, skewness and Jarque Bera test for normality are shown in table 1.

Table 1: Data description

Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque bera	Probability
6.68E-05	0.103861	-0.102622	0.007853	-0.062969	38.15756	103108.9	0.000000

The NSE 20 share index natural logarithm ranged between 0.103861 and -0.102622 with a mean of 0.0000668. The Jarque Bera test was 103108.9 with a p-value of 0.00000. Since the probability value was less than 0.01, we concluded that the NSE return series is not normally distributed. The negative skewness value of -0.062969 implied that the series had a long left tail. The return series was leptokurtic since the value of kurtosis was 38.15756 which was greater than 3 for normal distribution. This was also represented in figure 2.

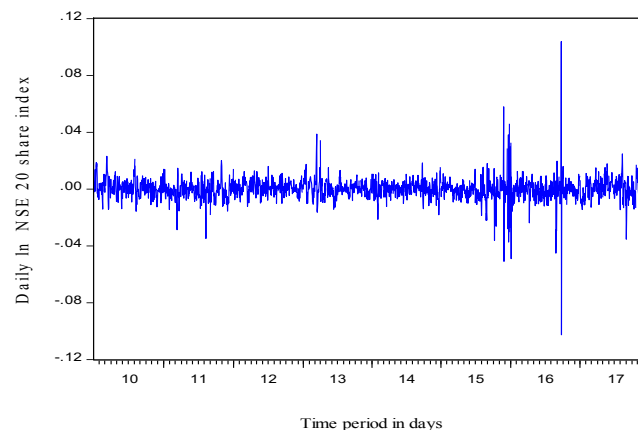


Figure 2: Natural logarithms of NSE 20 share index for 04/01/2010-29/12/2017

The NSE 20 share index trends suggested presence of structural breaks. We therefore tested for multiple structural breaks endogenously using Bai and Perron (1998) test and found four significant breaks at 07/12/2011, 13/3/2013, 03/3/2015 and 31/8/2016 using Global L breaks versus none.

Table 2: Chow breakpoint test

F statistic	7.002724***	Prob F(4,1997)	0.0000
Log likelihood ratio	27.88591***	Prob Chi-square (4)	0.0000
Wald statistic	28.01090***	Prob. Chi Square(4)	0.0000

*** indicates statistically significant at 1% level of significance

Source: Authors

In order to confirm the presence of the breaks, we run the four dates on a Chow breakpoint test as shown in table 2 and confirmed the presence of the breaks since the F statistic, Log likelihood ratio and Wald statistic were greater than the critical values. We therefore rejected the null hypothesis of no breaks at specified breakpoints in favor of structural breaks at the four dates. The four breakpoints led to the data being subdivided into six period as shown in table 3.

Table 3: Study period with structural breakpoints

Period	Time frame	No of Observations
Full period	04/01/2010-29/12/2017	2002
Sub-period 1	04/01/2010-06/12/2011	489
Sub-period 2	07/12/2011-12/03/2013	317
Sub-period 3	13/3/2013- 02/3/2015	490
Sub-period 4	03/3/2015-30/8/2016	377
Sub-period 5	31/8/2016-29/12/2017	329

Source: Authors

Stationarity test

Stationarity tests were done for all period as shown in table 4. Since the KPSS LM values for all periods were smaller than the critical values at all levels of significance, we did not reject the null hypothesis of the series being stationary. We concluded that the series were stationary. However, sub period 1 was differenced once to achieve the stationarity thus integrated of order I(1).

Table 4: Stationarity test

Period	KPSS				ADF			
	Critical values				Critical values			
	LM Values	1%	5%	10%	Test statistic	1%	5%	10%
Full period	0.315693***	0.739000	0.463000	0.347000	-26.24883***	-3.433420	-2.862783	-2.567478
Subperiod(1)	0.152670	0.739000	0.463000	0.347000	-10.35419***	-3.443551	-2.867255	-2.569876
	I(1)***							
Subperiod(2)	0.124652***	0.739000	0.463000	0.347000	-10.14358***	-3.450878	-2.870473	-2.571600
Subperiod(3)	0.127933***	0.739000	0.463000	0.347000	-15.87960***	-3.443496	-2.870473	-2.571600
Subperiod(4)	0.132769***	0.739000	0.463000	0.347000	-23.28761***	-3.443496	-2.870473	-2.571600
Subperiod(5)	0.134553***	0.739000	0.463000	0.347000	-12.58876***	-3.443496	-2.870473	-3.571600

*** Indicates acceptance and rejection respectively at 1% level of significance

Source: Authors

The stationarity was also confirmed by the ADF test, since the test statistics for all periods were less than the critical values at all levels of significance. We rejected the null hypothesis that the series had a unit root for the alternative hypothesis that the series was stationary.

Test for ARCH effects using ARCH Lagrange multiplier.

The series for all periods were tested for ARCH effect and the results presented in table 5. The LM statistic was large for all periods with a probability of 0.0000 thus significant at 1% level of significance. We rejected the null hypothesis of NO ARCH effects in favor of ARCH effects. We concluded that the NSE stock market return exhibited ARCH effects and thus justified our use of GARCH models.

Table 5: ARCH-LM test

Period	F- statistic	Prob F	Obs*R squared	Prob.Chi square(2)
Full period	28,22886	2,1999	54.98938***	0.0000
Sub-period 1	57.05536	2,486	92.98308***	0.0000
Sub-period 2	31.80047	2,314	53.39366***	0.0000
Sub-period 3	29.17004	2,487	52.41983***	0.0000
Sub-period 4	9.286127	2,374	17.83554***	0.0001
Sub-period 5	6.037021	2,326	11.74997***	0.0000

*** indicates significance at 1% level of significance

Source: Authors

Result and Discussion

After confirming the return series to be stationary and exhibiting ARCH effects, the data was run for GARCH, GARCH-M, EGARCH, TGARCH, and PGARCH in EVIEWS for all periods. The results for the GARCH(1,1) model are presented in table 6. The coefficients of the ARCH effects are positive and significant for all periods at 1% level of significance implying that news about past volatility had an explanatory power on current volatility. Similarly, the GARCH term was positive and significant for all periods except for the period December 2011 to March 2013 which was not significant implying that past volatility largely influenced current volatility.

Table 6: GARCH (1,1)

Coefficients	Subperiod(1)	Subperiod(2)	Subperiod(3)	Subperiod(4)	Subperiod(5)	Full period
MEAN EQUATION						
μ	-0.000296	0.001324***	0.000365*	-0.001718***	0.001690***	0.000296***
VARIANCE EQUATION						
ω	1.69E-05***	1.37E-05**	8.16E-06***	1.67E-05***	1.28E-05**	1.23E-05***
α	0.495078***	0.246924***	0.302945***	0.566435***	1.116822***	0.543127***
β	0.165339*	0.295139	0.426365***	0.397691***	0.264688***	0.356720***
$\alpha + \beta$	0.660417	0.542063	0.72931	0.964126	1.38151	0.899847
Log likelihood	1794.309	1216.117	1892.239	1281.327	1112	7211.028
AIC	-7.322327	-7.647426	-7.707097	-6.776272	-6.740911	-7.199828
SIC	-7.288034	-7.599995	-7.672857	-6.734551	-6.694758	-7.188636
HQC	-7.308858	-7.628480	-7.693650	-6.759712	-6.722499	-7.195719
ARCH LM test for heteroscedasticity						
Statistic	0.141706	0.919962	0.258796	0.007333	0.073084	9.33E-06
Probability	0.7066	0.3375	0.6109	0.9316	0.7869	0.9976

***, **, * Indicates significant at 1%, 5% and 10%

Source: Authors

The level of volatility persistence measured by the sum of the ARCH and GARCH parameters decreased significantly from January 2010 to March 2015 against the full period volatility persistence of 0.899847 implying that the structural breaks led to a reduction on the volatility persistence. The findings concurred with those of Mc Millan and Thupayagale (2011) who found that structural breaks reduced volatility persistence in African countries. Malik *et. al.*, (2005) also found that volatility persistence decreased when structural breaks are considered in Canada. Babikir *et. al.*, (2012) also found reduced volatility persistence in South Africa. However, for the period between March 2015 to December 2017 it increased beyond the full period volatility persistence thus exhibiting volatility as being explosive. The findings concur with those of Ahmed and Suliman (2011) who found explosive volatility in Sudan, Alagidede and Panagiotidis (2009) who found explosive volatility in African countries and Chege *et.al.*, (2014) and Maqsood *et.al.*, (2017) who also found explosive volatility in Kenya. The explosive volatility may have been caused by large divesture by foreign investors, low profitability that led to profit warnings by listed firms, reduced market turnover and macroeconomic and political risks towards the end of 2017 caused by the two electioneering periods in 2017 (Republic of Kenya, 2017).

The series for the full period showed moderate volatility persistence and was well specified since the ARCH LM statistic was significant at 1% level of significance unlike in the other periods.

The findings of the GARCH- M (1,1) model were closely related to the results in the GARCH(1,1) model except for the inclusion of a risk premium. However, no results were recorded for the period December 2011 to March 2013 as shown in table 7 since the system could not perform the square root of negative numbers prevalent in the series.

Table 7: GARCH-M(1,1) model

Coefficients	Subperiod(1)	Subperiod(2)	Subperiod(3)	Subperiod(4)	Subperiod(5)	Full period
MEAN EQUATION						
μ	-0.001239	NA	0.001950	-0.001831*	-0.000225	-0.000324
λ	0.158955	NA	-0.321709	0.015347	0.245547**	0.100015
VARIANCE EQUATION						
ω	1.82E-05***	NA	3.39E-06***	1.67E-05***	2.02E-05***	1.25E-05***
α	0.496614***	NA	0.296232***	0.567508***	1.395184***	0.555330***
β	0.131468	NA	0.421922***	0.396909***	0.053430	0.343046***
$\alpha + \beta$	0.628082	NA	0.718154	0.964417	1.448614	0.898376
Log likelihood	1794.668	NA	1893.425	1281.332	1116.881	7212.106
AIC	-7.319706	NA	-7.707859	-6.770993	-6.759155	-7.199906
SIC	-7.276840	NA	-7.665059	-6.718841	-6.701464	-7.185915
HQC	-7.302870	NA	-7.691049	-6.750223	-6.736140	-7.194769
ARCH LM test for heteroscedasticity						
Statistic	0.158315	NA	0.090941	0.009927	0.103037	0.004392
Probability	0.6907	NA	0.7630	0.9206	0.7482	0.9472

***, **, * Indicates significant at 1%, 5% and 10%

Source: Authors

The risk premium parameter was positive and insignificant for all periods except for August 2016 to December 2017. This implied that volatility had no significant impact on expected return, thus investors were not compensated for any additional risk they took in their investment. These findings concur with Banumathy and Azhagaiah (2015), who found positive and insignificant risk premium in India and Ogum *et al.* (2005), who also found insignificant risk premium at the NSE. This was different for the period starting August 2016 till December 2017 where investors were rewarded for additional risk evidenced by a positive and significant risk premium parameter at 5% level of significance. While, the NSE was resilient during that period, the electioneering period may have created a political risk for which investors demanded a higher return for the possible risk (Republic of Kenya, 2017). The findings concurred with those of Alagidede and Panagiotidis, (2009) who found presence of a risk premium in the African countries, and Chege *et al.* (2014), Ndwiiga and Muriu (2016) and Maqsood *et al.* (2017) who reported presence of a risk premium in Kenya. Since the ARCH term was positive and significant at 1% level of significance for all periods, news of previous volatility explained the current volatility. Past volatility of stock market return volatility was significant in influencing the current volatility for most of the study period as evidenced by positive and significant GARCH term parameter. However, this was not the case for the period between January 2010 to June 2011 and August 2016 to December 2017 as it was not significant at any level of significance. This may be due to the effects of the euro debt crisis in 2010 and the interest capping in Kenya in 2016 and the electioneering period in 2017 (Republic of Kenya, 2017). Just like in the GARCH model, the volatility persistence parameter decreased against the full period value of 0.898376 thus supporting the view of structural breaks reducing volatility persistence.

Table 8: EGARCH(1,1)

Coefficients	Subperiod(1)	Subperiod(2)	Subperiod(3)	Subperiod(4)	Subperiod(5)	Full period
MEAN EQUATION						
μ	-0.000383	0.001231***	0.000376*	-0.001353***	0.000944**	0.000278***
VARIANCE EQUATION						
ω	-5.682812***	-1.560181**	-3.341257***	-1.161863***	-2.200920***	-2.822541***
α	0.798817***	0.265885***	0.518273***	0.472492***	0.812570***	0.619346***
β	0.503508***	0.870524***	0.722110***	0.913724***	0.831797***	0.763458***
γ	0.007595	0.109259***	0.013916	0.196018***	-0.258140***	-0.007990
$\alpha + \beta$	1.302325	1.136409	1.240383	1.386216	1.644367	1.382804
Log likelihood	1794.668	1216.446	1892.742	1292.734	1123.409	7215.963
AIC	-7.320299	-7.643192	-7.705068	-6.831480	-6.798836	-7.203759
SIC	-7.277433	-7.583904	-7.662268	-6.779328	-6.741145	-7.189769
HQC	-7.303463	-7.619509	-7.688259	-6.810779	-6.775821	-7.198623
ARCH LM test for heteroscedasticity						
Statistic	0.158315	3.146234	0.215474	0.728764	0.009440	0.029339
Probability	0.6907	0.0761	0.6425	0.3933	0.9226	0.8640

***, **, * Indicates significant at 1%, 5% and 10%

Source: Authors

The findings also concurred with those of GARCH model in that volatility persistence was explosive for the period between August 2016 to December 2017. The GARCH-M model was well specified at 5% level of significance as shown by the Arch LM statistic. In

the EGARCH(1,1) model, the ARCH effect parameter was positive and significant for all periods at 1% level of significance as shown in table 8. This implied that current volatility was explained by previous news of volatility while past volatility of stock market return volatility was significant in influencing current volatility. This was shown by the GARCH effect term being positive and significant at 1% level of significance for all periods.

The sum of ARCH and GARCH effect terms was greater than one for all periods implying that volatility persistence was highly explosive during the study period. This means that any shocks in the market would lead to a permanent change in all future values of volatility. Similar to the GARCH and GARCH-M models, the volatility persistence decreased against the full period persistence of 1.382804 for the period January 2010 to March 2015, implying a reduction in volatility persistence with structural breaks. However, volatility persistence for the period March 2015 to December 2017 increased beyond the 1.382804. There was presence of leverage effects in the NSE for the period August 2016 to December 2017. This implied that bad news increased volatility than good news. This may be explained by the interest caping in Kenya that affected listed banks profitability and the political environment in Kenya following the two elections in 2017 (Republic of Kenya, 2017). The findings concurred with those of Gourdarzi and Ramanarayan (2010) in India, Mekoya(2013), Wagalla *et.al.*(2011), Ogum *et.al.*(2005) and Ombamba (2015) in Kenya who also studied the market and found leverage effects in the NSE. This leverage effect could also explain the explosive volatility experienced in that period.

The leverage effect term was positive and significant at 1% level of significance for the period December 2011 to March 2013 and March 2015 to August 2016 implying that positive shocks increased volatility than negative shocks. During the full period, the NSE did not exhibit significant leverage effects. These findings concurred with those of Nyamongo and Misati (2010), who found the NSE to have insignificant leverage effects using EGARCH. The EGARCH model for the full period did not significantly capture the ARCH effects as shown by the ARCH LM statistic. In addition, the EGARCH model was prevalent at exhibiting explosive volatility. This is explained by its exponential growth on the conditional variance where it overweighs the effects of larger shocks to volatility(Engle and Ng,1993).

The results of TGARCH (1,1) model are shown in table 9. The ARCH effect term was positive and significant implying that one can explain the current volatility from the news of previous volatility. The GARCH effect term was also positive and significant thus current volatility was significantly influenced by past volatility.

Table 9: TGARCH(1,1)

Coefficients	Subperiod(1)	Subperiod(2)	Subperiod(3)	Subperiod(4)	Subperiod(5)	Full period
MEAN EQUATION						
μ	-0.000300	0.001303***	0.000376*	-0.001260***	0.001018***	0.000260*
VARIANCE EQUATION						
ω	1.69E-05***	7.22E-06	8.23E-08***	1.50E-05***	1.51E-05***	1.24E-05***
α	0.487142***	0.245442***	0.320808***	0.984737***	0.461924**	0.508922***
β	0.162961*	0.596786***	0.422307***	0.423231***	0.260380***	0.352377***
γ	0.019434	-0.165220**	-0.030969	-0.808483***	1.109097***	0.071308
$\alpha + \beta$	0.650103	0.842228	0.743115	1.407968	0.722304	0.861299
Log likelihood	1794.318	1217.210	1892.289	1291.552	1119.936	7211.461
AIC	-7.318273	-7.648014	-7.703219	-6.825208	-6.777728	-7.199261
SIC	-7.275406	-7.588725	-7.660418	-6.773056	-6.720037	-7.185271
HQC	-7.301436	-7.624331	-7.686407	-6.804507	-6.754714	-7.194125
ARCH LM test for heteroscedasticity						
Statistic	0.125126	1.557628	0.250454	0.002361	0.002009	0.000991
Probability	0.7235	0.2120	0.6168	0.9612	0.9643	0.9749

***, **, * Indicates significant at 1%, 5% and 10%

Source: Authors

The findings on the volatility persistence concurred with those in the GARCH, GARCH-M and EGARCH models which found that volatility persistence reduced against the full sample volatility persistence of 0.861299 for the period January 2010 to March 2015. The findings supported the view that structural breaks reduce volatility persistence. Volatility persistence increased for the period March 2015 to August 2016 against that for the full sample which supports the findings of the other models in the study. However, they differed in that, for the period August 2016 to December 2017 the volatility persistence parameter decreased against the full period value of 0.861299.

The market exhibited presence of leverage effect for the period August 2016 to December 2017. This was signified by a positive and significant value of 1.109097 at 1% level of significance. This means that during that period, bad news increased volatility more than good news. This may be explained by the interest caping in Kenya that affected listed banks profitability and the political environment in Kenya following the two elections in 2017 (Republic of Kenya, 2017). During the full period the market did not exhibit leverage

effects. These findings concurred with those of the EGARCH model. The TGARCH(1,1) model for the full sample was well specified at 5% level of significance as shown by the ARCH LM statistic.

The ARCH effect term for the PGARCH(1,1) model was positive and significant at 1% level of significance as shown in table 10 for all periods. This implied that past news of volatility had an explanatory power on current volatility except for the period starting December 2011 to March 2013 where it was positive but insignificant.

Table 10: PGARCH(1,1)

Coefficients	Subperiod(1)	Subperiod(2)	Subperiod(3)	Subperiod(4)	Subperiod(5)	Full period
MEAN EQUATION						
μ	-0.000311	0.001234***	0.000373*	-0.001340	0.001092***	0.000368***
VARIANCE EQUATION						
ω	7.80E-05	5.61E-11	0.000175	3.87E-11	0.021498	0.001680
α	0.482309***	0.237500	0.302211***	0.793645***	0.438261***	0.407158***
β	0.185294*	0.038107	0.459642***	0.139912	0.481750***	0.458768***
γ	0.008329	-0.237500	-0.034882	-0.422061***	0.288592***	0.007803
δ	1.700908***	4.415712	1.415913***	4.589986**	0.444244***	1.007431***
$\alpha + \beta$	0.667603	0.275607	0.761853	0.933557	0.920011	0.865926
Log likelihood	1794.410	1219.828	1892.494	1293.772	1127.972	7223.136
AIC	-7.314561	-7.658222	-7.699975	-6.831684	-6.820501	-7.209926
SIC	-7.263121	-7.587075	-7.648615	-6.769101	-6.751272	-7.193137
HQC	-7.294357	-7.629802	-7.679804	-6.806843	-6.792883	-7.203762
ARCH LM test for heteroscedasticity						
Statistic	0.257782	0.028311	0.118421	0.118023	2.307739	1.016302
Probability	0.6116	0.8664	0.7308	0.7312	0.1287	0.3134

***, **, * Indicates significant at 1%, 5% and 10%

Source: Authors

The GARCH term effect was positive and significant at 1% and 10% level of significance for the first, third, fifth subperiods and the full period. This implied that past volatility can be used to explain the current volatility. However, in the second and fourth subperiods, past volatility could not explain the current volatility. This could be due to the fewer observation in the two sub periods not being well captured by the model.

Similar to the other models in the study, volatility persistence decreased for the period between January 2010 to March 2015 against the full period value of 0.865926. This shows that including structural breaks in the model reduces volatility persistence. In addition, volatility persistence was explosive in the market for the period March 2015 to December 2017. The findings are similar to the findings of the other models in the study.

The market exhibited leverage effects at 1% level of significance during the period August 2016 to December 2017 where bad news increased volatility more than good news. On average there were no significant leverage effects in the full period. The findings also concurred with those of the EGARCH and TGARCH models in the study.

On estimating the power of the volatility estimate, the power parameter was largely 1 for three out of the six periods significant at 1% level of significance. This meant that conditional standard deviation was estimated instead of conditional variance. However, during the period March 2015 to August 2016, the power term was 5 at 5% level of significance and less than 1 for the period between August 2016 and December 2017 at 1% level of significance. During the period December 2011 to March 2013, the power parameter was insignificant. The PGARCH(1,1) for the full period did not capture the ARCH effects since its ARCH LM statistic was high at 1.016302.

Using Log likelihood method, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Hannan Quinn Criterion (HQ) values for the full sample, the best fit models for symmetric and asymmetric effects were selected. The model selected was also confirmed to have captured all the ARCH effects using the ARCH LM statistic and thus well specified. The best fit model to capture symmetric volatility in Kenya during the study period was found to be the GARCH (1,1) model at 1% level of significance. The findings concurred with Gourdarzi and Ramanarayan, (2010) and Achia *et. al.*, (2013), who found that GARCH model is the best fit model for Indian and Kenyan stock markets respectively. On the other hand TGARCH(1,1) model was the best fit model to capture asymmetric effects on the Nairobi Securities Exchange. The findings concurred with Banumathy and Azhagaiah(2015) who found TGARCH to be the best fit model in India and Maqsood *et. al.*, (2017) who found that TGARCH model is best fit to capture the asymmetric effects of the Nairobi Securities Exchange.

Findings and Implications

The study aimed at modeling the Nairobi Securities Exchange stock market return volatility in the presence of structural breaks. The NSE market was found to be stationary and to exhibit ARCH effects. The market is thus said to demonstrate non normal distribution, the series was skewed to the left and it showed evidence for a leptokurtic distribution. Past volatility was found to have a significant impact on current volatility, implying that market return can be forecasted. On further analysis using GARCH type models, it was revealed that the NSE stock market exhibit volatility clustering and volatility persistence. The volatility persistence was found to reduce when structural breaks were incorporated in the model. However, presence of leverage effects increased the volatility persistence and the EGARCH model was prevalent at exhibiting explosive volatility for all periods unlike the other models in the study due to its exponential growth on the conditional variance. In addition, investors were not rewarded for taking up additional risk since the risk premium was largely insignificant. However, in periods of explosive volatility, the investors were rewarded for any additional risk taken. Moreover, the market was generally found not to exhibit significant leverage effects during the study period. We found that leverage effect, volatility persistence and risk premium were correlated. The GARCH (1,1) was found to be the best fit model to test for symmetric effects while TGARCH (1,1) was found to be the best fit model to test for asymmetric effects at the NSE. This is because they had the lowest values for all information criteria and were well specified in regards to the ARCH effects.

Conclusions

Following the hypothesis testing, this study concludes that the Nairobi Securities Exchange exhibited stylized facts during the study period. This includes volatility clustering, non-normality and volatility persistence but did not significantly exhibit leverage effects and risk premium. It found that the best fit models to capture symmetric and asymmetric effects were GARCH(1,1) and TGARCH(1,1) respectively. In addition volatility persistence was found to reduce when structural breaks were incorporated in the model. The study found that there exist a relationship between leverage effects, explosive volatility and risk premium at the NSE.

While the GARCH models were able to provide evidence for the stylized facts in the NSE, we conclude that the presence or absence of these features is period specific. These relates especially to volatility persistence, leverage effects and risk premium effects. Caution should therefore be taken in using a specific GARCH model to forecast market return volatility especially EGARCH model as it was found to overstate volatility persistence. We therefore recommend pretesting the data before any volatility forecasting is done on the NSE.

The findings of this study are crucial for policy makers in their use of forecasted market return volatility in the valuation of derivatives as a measure of mitigating risk. The findings will also benefit financial analyst and researchers who use GARCH models to forecast market return volatility. The study findings can be extended by testing the impact of structural breaks using other models like the neural networks methods.

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